We claim:

1   1.   A method for classifying cardiography data, comprising the step of:

2   applying a kernel transform to sensed data acquired from sensors sensing electromagnetic heart activity,

3   resulting in transformed data, prior to classifying said transformed data using machine learning.

1   2.   The method of claim 1, further comprising the step of:

2   converting said sensed data into a wavelet domain using a wavelet transform, prior to applying said kernel

3   transform.

1   3.   The method of claim 1, for classifying magneto-cardiography data, further comprising the step of:

2   acquiring said sensed data from magnetic sensors proximate a patient's heart.

1   4.   The method of claim 2, for classifying of magneto-cardiography data, further comprising the step of:

2   acquiring said sensed data from magnetic sensors proximate a patient's heart.

1   5.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using machine learning.

1   6.   The method of claim 2, further comprising the step of:

2   classifying said transformed data using machine learning.

1   7.   The method of claim 3, further comprising the step of:

2   classifying said transformed data using machine learning.

1   8.   The method of claim 4, further comprising the step of:

2   classifying said transformed data using machine learning.

1   9.   The method of claim 1, said kernel transform satisfying Mercer conditions.

1   10.   The method of claim 1, said kernel transform comprising a radial basis function.

1   11.   The method of claim 1, said step of applying a kernel transform comprising the steps of:

2   assigning said transformed data to a first hidden layer of a neural network;

3   applying training data descriptors as weights of said first hidden layer of said neural network; and

4   calculating weights of a second hidden layer of said neural network numerically.

1   12.   The method of claim 11, said step of calculating said weights of said second hidden layer numerically

2   further comprising the step of:

3   calculating said weights of said second hidden layer using kernel ridge regression.

1   13.   The method of claim 1, said step of applying a kernel transform comprising the step of:

2   applying a direct kernel transform.

1   14.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using a self-organizing map (SOM).

1   15.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using a direct kernel self-organizing map (DK-SOM).

1   16.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using kernel partial least square (K-PLS) machine learning.

1   17.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using direct kernel partial least square (DK-PLS) machine learning.

1   18.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using a least-squares support vector machine (LS-SVM).

1   19.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using a direct kernel principal component analysis (DK-PCA).

1 20.   The method of claim 1, further comprising the step of:

2   classifying said transformed data using a support vector machine (SVM / SVMLib).

1 21.   The method of claim 20, said step of classifying said transformed data using a support vector machine

2 (SVM / SVMLib) further comprising the step of:

3   setting an SVMLib regularization parameter, C, to C=1/λ, for an n data kernel, wherein:

4   said λ is proportional to said n to a power of 3/2

1 22.   The method of claim 20, said step of classifying said transformed data using a support vector machine

2 (SVM / SVMLib) further comprising the step of:

3   setting an SVMLib regularization parameter, C, to C=1/λ, for an n data kernel, wherein:

4
$$\lambda = \min\left\{1; \left(\frac{n}{1500}\right)^{\frac{3}{2}}\right\}.$$

1 23.   The method of claim 2, said step of converting said sensed data into a wavelet domain comprising the step

2 of:

3   applying a Daubechies wavelet transform to said sensed data.

1 24.   The method of claim 2, further comprising the step of:

2   selecting features from said wavelet data which improve said classification of cardiography data.

1 25.   The method of claim 24, said step of selecting said features further comprising the step of:

2   eliminating selected undesirable features from said wavelet data.

1 26.   The method of claim 25, said step of eliminating selected undesirable features comprising the step of:

2   eliminating outlying data from said wavelet data.

1 27.   The method of claim 25, said step of eliminating selected undesirable features comprising the step of:

2   eliminating cousin descriptors from said wavelet data.

1 28.   The method of claim 24, said step of selecting said features further comprising the step of:

2   retaining only selected desirable features from said wavelet data.

1 29.   The method of claim 28, said step of retaining only selected desirable features further comprising the steps

2 of:

3   using a training data set; and

4   using a validation data set for confirming an absence of over-training of said training set.

1 30.   The method of claim 29, said step of retaining only selected desirable features further comprising the steps\

2 of:

3   using a genetic algorithm to obtain an optimal subset of features from said training data set; and

4   using said genetic algorithm for evaluating performance on said validation date set.

1 31.   The method of claim 29, said step of retaining only selected desirable features further comprising the steps\

2 of:

3   measuring sensitivities of said features from said wavelet data in relation to a predicted responses of said

4 features; and

5   eliminating lower-sensitivity features from among said features with comparatively lower sensitivity than

6 other, higher-sensitivity features from among said features.

1 32.   The method of claim 24, said step of selecting said features further comprising the steps of:

2   eliminating selected undesirable features from said wavelet data; and

3   retaining only selected desirable features from said wavelet data.

1   33.   The method of claim 1, further comprising the step of:
2   normalizing said sensed data.
1   34.   The method of claim 33, said step of normalizing said sensed data comprising the step of:
2   Mahalanobis scaling said sensed data.
1   35.   The method of claim 1, further comprising the step of:
2   centering a kernel of said kernel transform.
1   36.   The method of claim 35, said step of centering said kernel comprising the steps of:
2   subtracting a column average from each column of a training data kernel;
3   storing said column average for later recall, when centering a test data kernel.
4   subtracting a row average form each row of said training data kernel.
1   37.   The method of claim 36, said step of centering said kernel further comprising the steps of:
2   adding said stored column average to each column of said test data kernel;
3   for each row, calculating an average of said test data kernel; and
4   subtracting said row average from each horizontal entry of said test data kernel.
1   38.   An apparatus for classifying cardiography data, comprising computerized storage, processing and
2   programming for :
3   applying a kernel transform to sensed data acquired from sensors sensing electromagnetic heart activity,
4   resulting in transformed data, prior to classifying said transformed data using machine learning.
1   39.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   converting said sensed data into a wavelet domain using a wavelet transform, prior to applying said kernel
3   transform.
1   40.   The apparatus of claim 38, for classifying magneto-cardiography data, further comprising an input for:
2   acquiring said sensed data from magnetic sensors proximate a patient's heart.
1   41.   The apparatus of claim 39, for classifying of magneto-cardiography data, further comprising an input for:
2   acquiring said sensed data from magnetic sensors proximate a patient's heart.
1   42.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using machine learning.
1   43.   The apparatus of claim 39, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using machine learning.
1   44.   The apparatus of claim 40, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using machine learning.
1   45.   The apparatus of claim 41, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using machine learning.
1   46.   The apparatus of claim 38, wherein kernel transform satisfies Mercer conditions.
1   47.   The apparatus of claim 38, said kernel transform comprising a radial basis function.
1   48.   The apparatus of claim 38, said computerized storage, processing and programming for applying a kernel
2   transform further comprising computerized storage, processing and programming for:
3   assigning said transformed data to a first hidden layer of a neural network;
4   applying training data descriptors as weights of said first hidden layer of said neural network; and
5   calculating weights of a second hidden layer of said neural network numerically.

1   49.   The apparatus of claim 48, said computerized storage, processing and programming for calculating said
2   weights of said second hidden layer numerically further comprising computerized storage, processing and
3   programming for:
4   calculating said weights of said second hidden layer using kernel ridge regression.

1   50.   The apparatus of claim 38, said computerized storage, processing and programming for applying a kernel
2   transform further comprising computerized storage, processing and programming for:
3   applying a direct kernel transform.

1   51.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using a self-organizing map (SOM).

1   52.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using a direct kernel self-organizing map (DK-SOM).

1   53.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using kernel partial least square (K-PLS) machine learning.

1   54.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using direct kernel partial least square (DK-PLS) machine learning.

1   55.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using a least-squares support vector machine (LS-SVM).

1   56.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using a direct kernel principal component analysis (DK-PCA).

1   57.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   classifying said transformed data using a support vector machine (SVM / SVMLib).

1   58.   The apparatus of claim 57, said computerized storage, processing and programming for classifying said
2   transformed data using a support vector machine (SVM / SVMLib) transform further comprising computerized
3   storage, processing and programming for:
4   setting an SVMLib regularization parameter, C, to C=1/λ, for an n data kernel, wherein:
5   said λ is proportional to said n to a power of 3/2

1   59.   The apparatus of claim 57, said computerized storage, processing and programming for classifying said
2   transformed data using a support vector machine (SVM / SVMLib) transform further comprising computerized
3   storage, processing and programming for:
4   setting an SVMLib regularization parameter, C, to C=1/λ, for an n data kernel, wherein:

5
$$\lambda = \min\left\{1; \left(\frac{n}{1500}\right)^{\frac{3}{2}}\right\}.$$

1   60.   The apparatus of claim 39, said computerized storage, processing and programming for converting said
2   sensed data into a wavelet domain comprising computerized storage, processing and programming for:
3   applying a Daubechies wavelet transform to said sensed data.

1   61.   The apparatus of claim 39, further computerized storage, processing and programming for:
2   selecting features from said wavelet data which improve said classification of cardiography data.

1   62.   The apparatus of claim 61, said comprising computerized storage, processing and programming for
2   selecting said features further comprising computerized storage, processing and programming for:
3   eliminating selected undesirable features from said wavelet data.

1   63.   The apparatus of claim 62, said comprising computerized storage, processing and programming for
2   eliminating selected undesirable features comprising computerized storage, processing and programming for:
3   eliminating outlying data from said wavelet data.

1   64.   The apparatus of claim 62, said computerized storage, processing and programming for eliminating
2   selected undesirable features comprising computerized storage, processing and programming for:
3   eliminating cousin descriptors from said wavelet data.

1   65.   The apparatus of claim 61, said computerized storage, processing and programming for selecting said
2   features further comprising computerized storage, processing and programming for:
3   retaining only selected desirable features from said wavelet data.

1   66.   The apparatus of claim 65, said computerized storage, processing and programming for retaining only
2   selected desirable features further comprising computerized storage, processing and programming for:
3   using a training data set; and
4   using a validation data set for confirming an absence of over-training of said training set.

1   67.   The apparatus of claim 66, said computerized storage, processing and programming for retaining only
2   selected desirable features further comprising computerized storage, processing and programming for:
3   using a genetic algorithm to obtain an optimal subset of features from said training data set; and
4   using said genetic algorithm for evaluating performance on said validation date set.

1   68.   The apparatus of claim 66, said computerized storage, processing and programming for retaining only
2   selected desirable features further comprising computerized storage, processing and programming for:
3   measuring sensitivities of said features from said wavelet data in relation to a predicted responses of said
4   features; and
5   eliminating lower-sensitivity features from among said features with comparatively lower sensitivity than
6   other, higher-sensitivity features from among said features.

1   69.   The apparatus of claim 61, said computerized storage, processing and programming for selecting said
2   features further comprising computerized storage, processing and programming for:
3   eliminating selected undesirable features from said wavelet data; and
4   retaining only selected desirable features from said wavelet data.

1   70.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   normalizing said sensed data.

1   71.   The apparatus of claim 70, said computerized storage, processing and programming for normalizing said
2   sensed data comprising computerized storage, processing and programming for:
3   Mahalanobis scaling said sensed data.

1   72.   The apparatus of claim 38, further comprising computerized storage, processing and programming for:
2   centering a kernel of said kernel transform.

1   73.   The apparatus of claim 72, said computerized storage, processing and programming for centering said
2   kernel comprising computerized storage, processing and programming for:
3   subtracting a column average from each column of a training data kernel;
4   storing said column average for later recall, when centering a test data kernel.
5   subtracting a row average form each row of said training data kernel.

1   74.   The apparatus of claim 73, said computerized storage, processing and programming for centering said
2   kernel further comprising computerized storage, processing and programming for:
3   adding said stored column average to each column of said test data kernel;

4   for each row, calculating an average of said test data kernel; and

5   subtracting said row average from each horizontal entry of said test data kernel.